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Evolution of emotions and learning – A neural network mode

Kozielska-Reid, Magdalena

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Evolution of emotions and learning – a neural network model

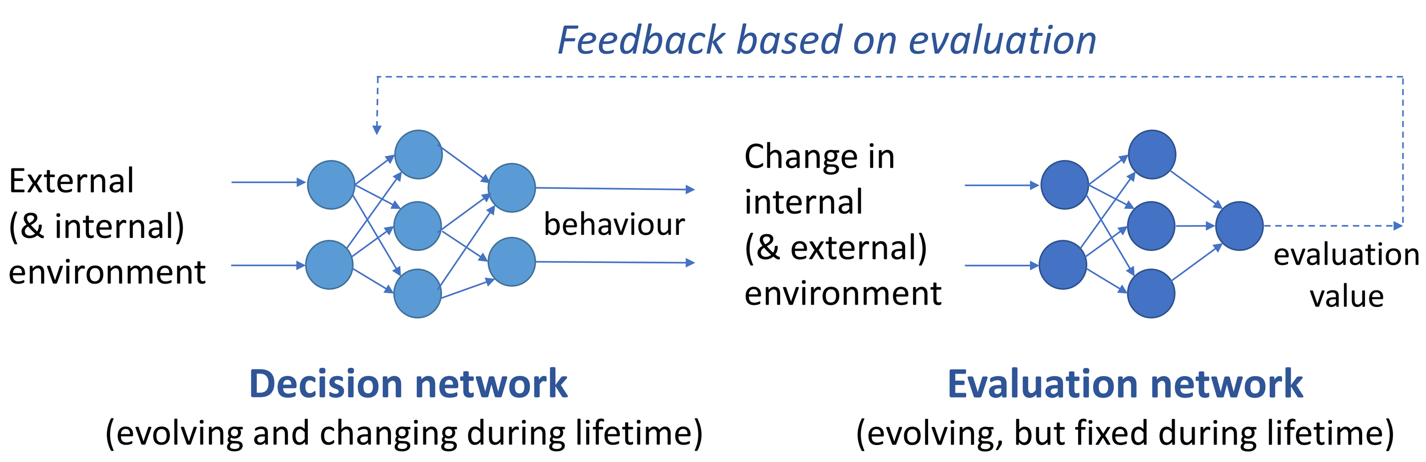
Magdalena Kozielska, Elles Jetten, Emiliano Méndez Salinas, Franjo Weissing

Groningen Institute for Evolutionary Life Sciences, University of Groningen, The Netherlands

m.a.kozielska@rug.nl

Introduction

Learning is an important adaptation that allows individuals to improve future decisions in the light of past experiences, but the evolution of learning is poorly understood. By means of a modelling approach, based on the evolution of neural networks, we try to shed light on the question how learning mechanisms are shaped by natural selection. This is a difficult task, since a learning mechanism must include (i) a decision mechanism that, depending on the environmental conditions, selects an action; (ii) an evaluation mechanism (like the emotional system) that assesses the implications of previous actions; and (iii) a feedback mechanism that modifies the decision mechanism in light of this evaluation.



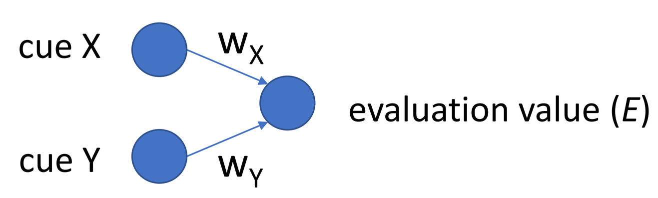
We hypothesize that the evaluation mechanism (i.e., the emotional system) predates the learning system, and that it has been adopted later during the evolution of learning. We therefore first investigate how such an evaluation mechanism might evolve. Assuming that the initial function of the evaluation mechanism was to assess environmental conditions (that are perceived by cues) as to their fitness consequences for the organism, we ask the questions:

How readily will an evaluation network evolve that is able to judge the fitness consequences of environmental situations based on simple environmental cues?

Methods overview

We consider the evolution of a neural network that perceives environmental cues, processes this information, and produces an evaluation value *E* as an output. The organism in question evaluates various environmental situations and makes choices (e.g., in what habitat to settle) based on this evaluation. These choices are fitness-relevant. Therefore, the networks will be selected whose evaluation value most closely aligns with the fitness to be expected in a given environment.

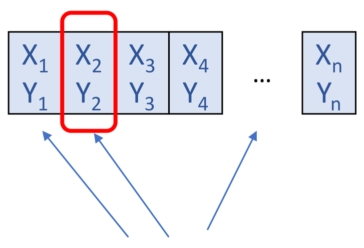
Here, we present the results for extremely simple networks like



In the above example, w_X and w_Y are heritable parameters that are transmitted from parents to their offspring (subject to rare mutations), thus allowing their evolution.

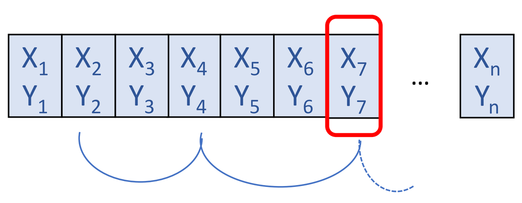
We consider two scenarios for decision making:

Scenario I – Simultaneous assessment



Individuals evaluate a subset of *k* options and choose the one with the highest evaluation value *E*.

Scenario II – Consecutive assessment



Individuals evaluate one option at a time and decide on whether to accept this option or to move on to another option (without return). Prob(staying) = Logistic function of *E*.

To fix ideas, we consider a patch choice situation, where X and Y provide information on the food abundance *F* and the number *P* of predators in the patch, respectively. Food abundance is proportional to fecundity, while predation reduces viability. Assuming a fixed mortality *m* induced per predator, we assume that fitness is given by $W(F,P) = (1-m)^P \cdot F$. In the competition scenario (considered later), *F* is divided by the number of consumers that have chosen the patch.

Results 1 – Reliable cues, no competition

First we consider the simplest situation where there is no competition within a patch and where cues provide reliable information on food abundance and predator number (X=*F* and Y=*P*).

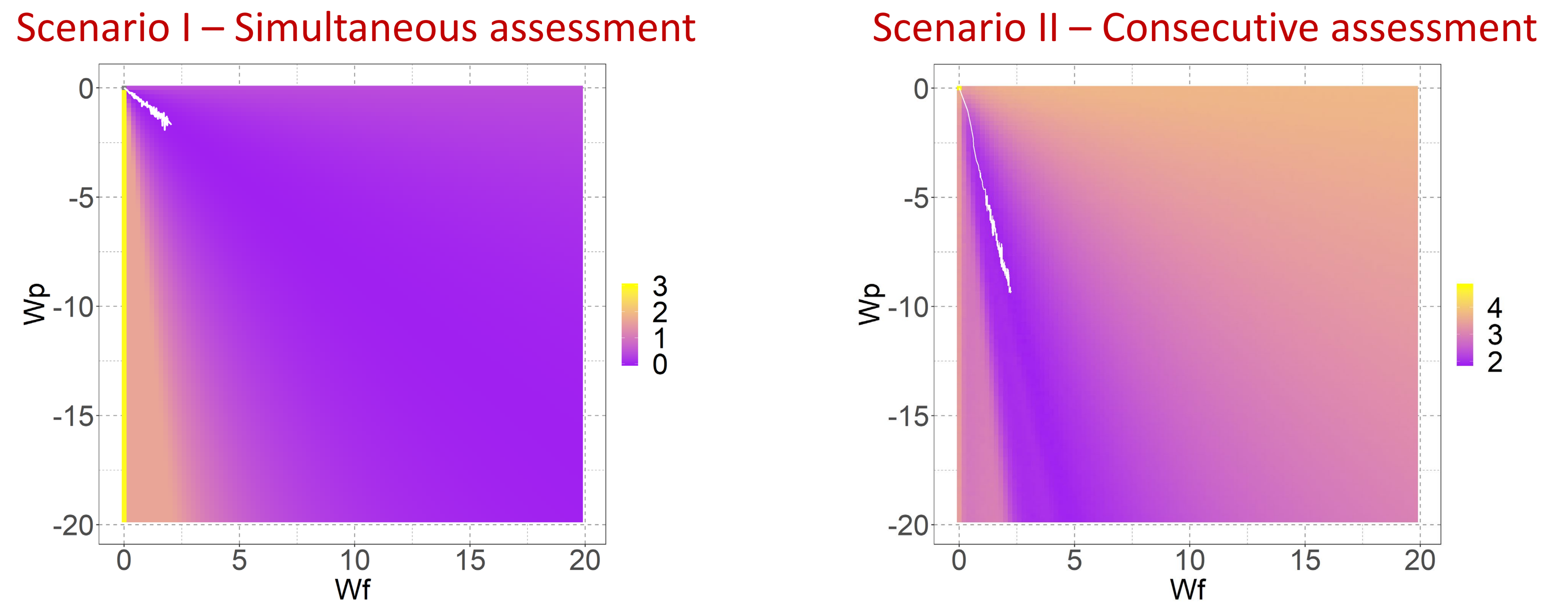


Fig. 1: Fitness landscape for a range of evaluation networks (characterized by the heritable parameters w_f and w_p) and a representative evolutionary trajectory (white). The heat map is based on the average fitness loss (= the difference between the fitness of the chosen patch and the fitness of the best available patch).

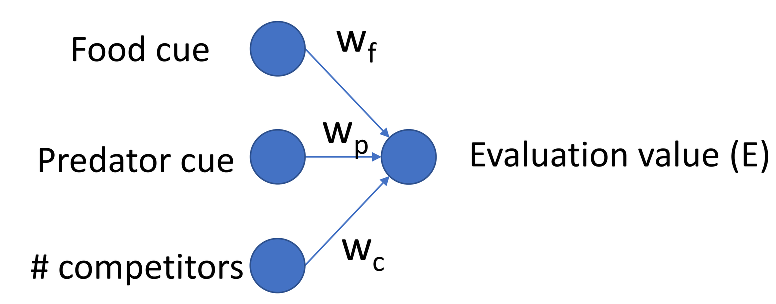
In case of simultaneous assessment, the fitness landscape is largely very flat, implying that wide range of networks can make almost optimal choices (fitness loss ≈ 0). Accordingly, singling out the highest-fitness patch among a set of *k* patches seems an easy (and easily evolving) task. In case of consecutive assessment, only networks with a fixed ratio w_f/w_p show optimal performance. No surprisingly, the fitness achieved in Scenario II is typically lower than that in Scenario I.

Conclusions:
A simple and effective evaluation system readily evolves. The way of decision-making strongly affects the fitness landscape and, hence, the evolutionary outcome.

Results 2 – Effects of competition

Here we investigate the situation where the individuals in a given patch have to share the food. Hence, competition is intense in 'popular' patches. Selection for competition avoidance might therefore lead to the coexistence of alternative evaluation systems. We investigated two cases:

1. When evaluating a patch, individuals use the simple network discussed above, not considering the number of competitors in the patch.
2. Individuals use an extended network (right) that bases the evaluation also on the number of competitors already present in the patch.



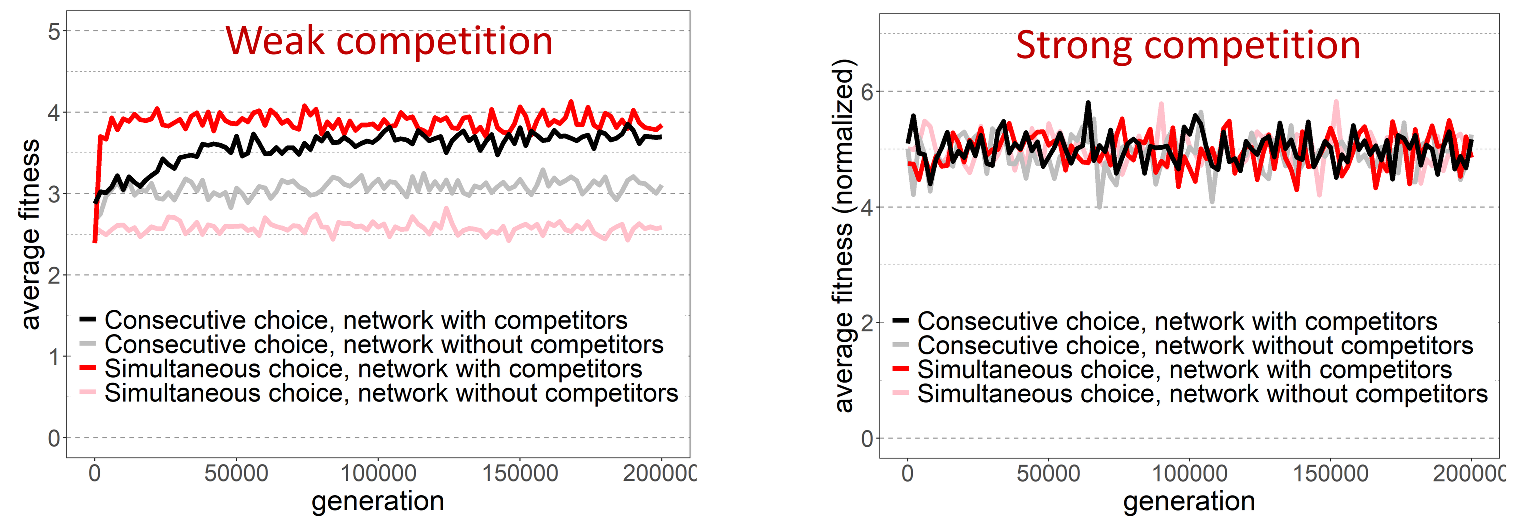


Fig. 2: Effect of choice scenario (consecutive or simultaneous) and network structure (simple or extended) on population fitness. Differences are small when competition is strong (on average many individuals per patch) but substantial when selection is weak.

Simulation outcomes only differ substantially when competition is weak. In that case, the extended network provides a clear fitness benefit in comparison to the simple network. Interestingly, for the simple network consecutive choice leads to a higher population fitness than simultaneous choice.

Polymorphism

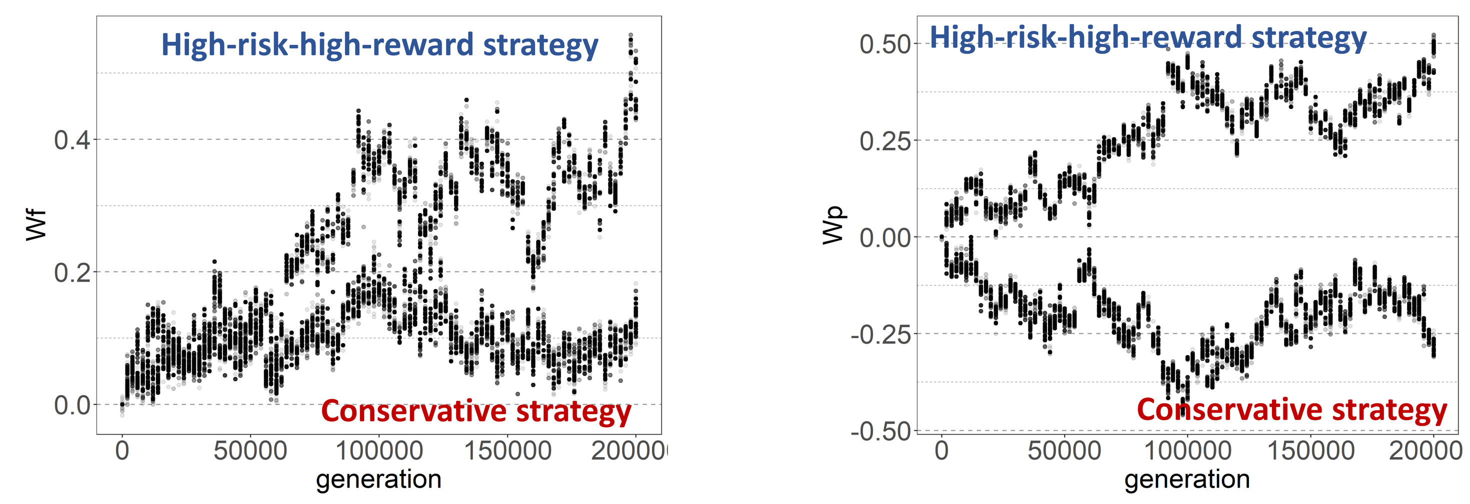


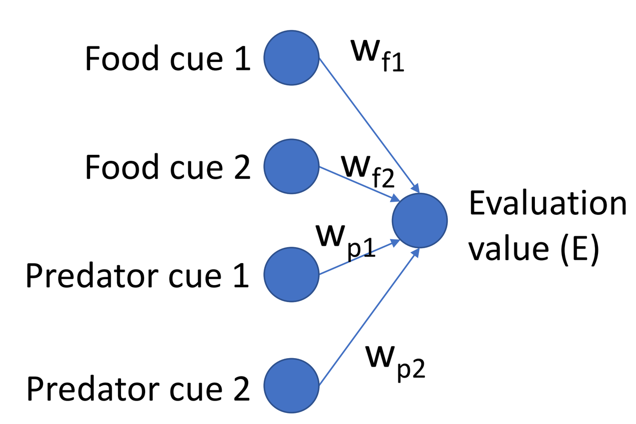
Fig. 3: Emergence of polymorphism. Each dot represents the weighing factor of one individual. Two clearly distinguishable strategies stably coexist. [Simultaneous assessment, simple network, weak competition.]

In a (small) number of simulations with simultaneous assessment, a polymorphism of alternative evaluation networks did emerge. Fig. 3 illustrates the coexistence of a 'conservative' evaluation network (red: negative w_p, i.e., avoidance of predators) and a 'high-risk-high-reward' evaluation network (blue: seeking predator-infected patches that are avoided by conservative individuals).

Conclusions:
Competition among consumers has a clear effect on the evolution of an evaluation system. When competition is weak, extended networks using additional information have a selective advantage. Competition avoidance may select for a polymorphism of alternative evaluation networks.

Results 3 – Cues with limited information content

Cues perceived by individuals may not precisely reflect the environment and more than one cue may be present. Here, we vary the precision of the cues both for predator number and food abundance. The cue perceived by an individual is taken from a normal distribution around the real environmental value; cue precision is inversely related to the standard deviation of this distribution.



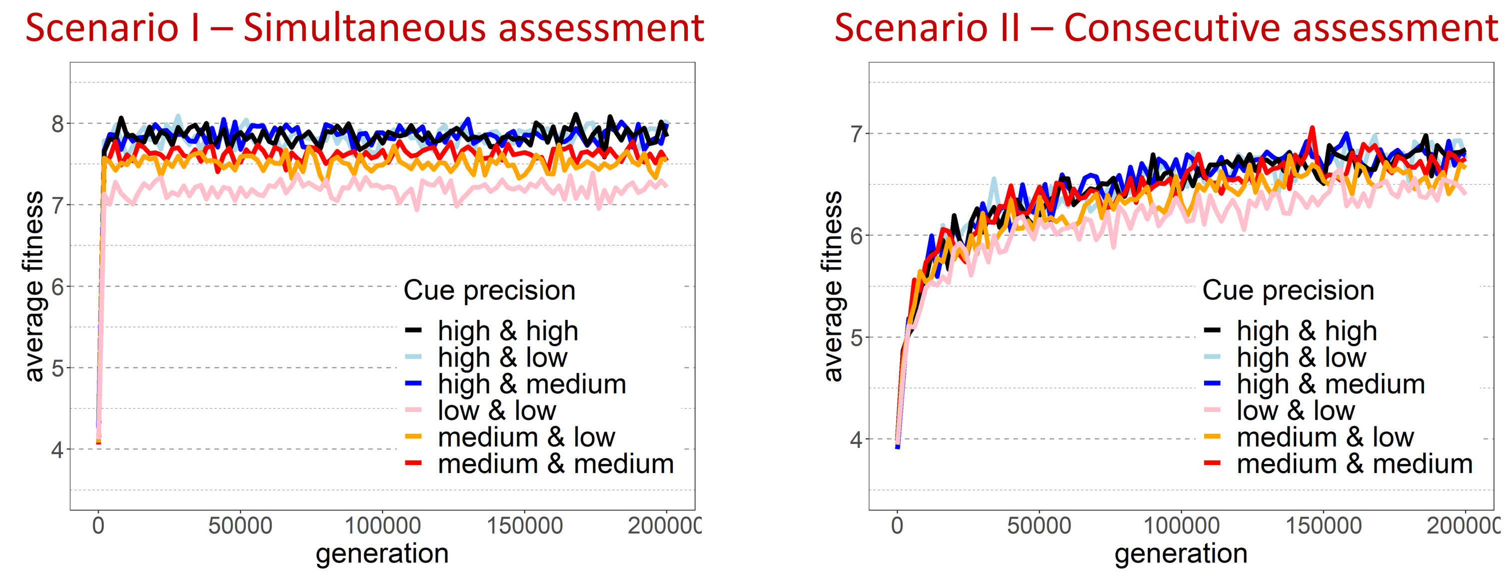


Fig. 4: Effect of cue precision on population fitness. A label like 'high & medium' indicates a simulation where one of the food cues (resp. predator cues) is of high precision while the other is of medium precision.

When cues differ a lot in precision, only the high-precision cue is used by the evolved evaluation network. When the difference in precision is small, a weighted average of the cues is used, resulting in a clearly enhanced performance of the network.

Conclusions:
When several cues are present, the low precision of cues can be compensated by using a weighted average of the cues.

General conclusion:

Surprisingly simple networks are able to accurately evaluate environments as to their fitness consequences. Hence effective learning may be based on a relatively simple emotional system.